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Original Research

Hybrid neuro fuzzy inference systems for simulating catchment sediment yield

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ABSTRACT

Increasing sediment yield is one of the important environmental challenges in river basins resulting from changing land use. The current study develops an adaptive neuro fuzzy inference system (ANFIS) hybridized with evolutionary algorithms to predict annual sediment yield at the catchment scale considering some key factors affecting the alteration of the sediment yield. The key factors consist of the area of the sub-catchments, average slope of the sub-catchments, rainfall, and forest index, and the output of the model is sediment yield. Several indices such as the Nash–Sutcliffe efficiency (NSE), root mean square error and vulnerability index (VI) were applied to evaluate the performance of the models. Moreover, hybrid models were compared in terms of complexities to select the best approach. Based on the results in Talar River basin in Iran, several hybrid models in which particle swarm optimization (PSO), genetic algorithm, invasive weed optimization, biogeography-based optimization, and shuffled complex evolution used to train the neuro fuzzy network are able to generate reliable sediment yield models. The NSE of all previously listed models is more than 0.8 which means they are robust for assessing sediment yield resulting from land use change with a focus on deforestation. The proposed models are fairly similar in terms of computational complexities which implies no priority for selecting the best model. However, PSO-ANFIS performed slightly better than the other models especially in terms of accuracy of the outputs due to a high NSE (0.92) and a low VI (1.9 Mg/ha). Using the proposed models is recommended due to the lower required time and data compared to a physically based models such as the The Soil and Water Assessment Tool. However, some drawbacks restrict the application of the proposed model. For example, the proposed models cannot be used for small temporal scales.

1. Introduction

Environmental challenges in river basins have been extensively addressed in the literature due to the critical importance of mitigating ecological impacts in the river and lake ecosystems. Water quality is one of the key factors among all environmental variables in a river ecosystem (Quadroni et al., 2022). Hence, water quality modeling at different spatial and temporal scales has been highlighted in previous studies (e.g., Fu et al., 2019). A water quality model could be developed at the catchment scale or river reach scale. Generally, using water quality models at the catchment scale could be useful for estimating impacts of human activities on a river ecosystem at a larger scale which might be helpful for policy makers and environmental managers to investigate land development scenarios. For example, land use change is one of the environmental challenges which might exacerbate water quality problems in river habitats. Among water quality factors in catchments, sediment yield is one of the key parameters due to extensive impacts on aquatic and terrestrial habitats.

The importance of assessing sediment yield in catchments has been highlighted (Dutta, 2016). Many efforts have been done to model sediment yield and reviewed in the literature (Pandey et al., 2016). One of the conventional approaches for simulating sediment yield as well as other water quality parameters is to apply hydrological models developed in recent decades. For instance, the Soil and Water Assessment Tool (SWAT) is one of these models which is able to work at the catchment scale (Gassman et al., 2014; Wang et al., 2019). This model is popular in the U.S. for assessing land management scenarios which could be installed as an extension of a geographical information system

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(GIS). A wide range of data should be inserted in the model generally including raster files and text files such as a land use map, weather data, etc. This type of model is advantageous for considering different temporal scales. However, such models might not be selected by many engineers especially in developing countries due to limitations in data collection and the considerable budget required for implementing these models. Full discussion on the advantages/disadvantages of this type of model compared with other models have been addressed in the literature (Jimeno-Sáez et al., 2022).

Another option for simulating sediment yield as well as other water quality parameters is artificial intelligence (AI) methods which have been applied in different branches of science and engineering. AI methods apply previous experiences with each phenomenon to develop a model for simulating future scenarios. Given the remarkable abilities of these methods, they have been utilized in many problems of environmental engineering and these applications are currently being quickly expanded in different countries (Holzinger et al., 2020). It seems that AI methods could be a strong alternative to conventional hydrological models to assess environmental parameters at the catchment scale. AI methods have not only been used for water quality parameters, but they also have been applied to simulate water quantity such as flood flows at the outlet of catchments. More details regarding the application of AI methods in water resources and environmental engineering have been extensively addressed in the literature (Al Aani et al., 2019; Nishant et al., 2020; Tung & Yaseen, 2020; Yaseen et al., 2019). Thus, it seems that capabilities of AI-based methods have been corroborated in environmental engineering which means using AI methods in many cases and problems is imaginable.

Generally, supervised machine learning models as a known AI-based method have been categorized as the classification methods and/or regression methods. Classification models such as support vector machine (SVM) are able to classify a parameter, if the nature of the parameter is classifiable (Dey et al., 2020). In contrast, if assessing the exact value of a parameter is the goal, using regression machine learning models is recommended. A review on benchmarking classification and regression models has been presented by Hoffmann et al. (2019).

Neural networks are one of the best known and popular machine learning models in which a computational map between inputs and output(s) can be generated. In fact, these networks consist of at least three layers including an inputs layer, one hidden layer, and the output layer. However, the number of hidden layers could be more than one and many hidden layers in some cases. The theory and application of neural networks have been broadly reviewed in the literature (e.g., Samek et al., 2021). Given the drawbacks of common neural networks like feed forward neural networks such as acting like a black box, some solutions have been developed to promote these networks in recent decades. One of the solutions for increasing interpretability of neural networks is to put a neural network in a fuzzy inference system which is called adaptive neuro fuzzy inference system (ANFIS) (Karaboga & Kaya, 2019).

Some previous studies highlighted the application of machine learning models in sediment yield and sediment transport as one of the key environmental factors for catchments (reviewed by Meshram et al., 2020). For example, suspended sediment load has been simulated through supervised machine learning models which indicated their capabilities for simulating cumulative sediment load (Adnan et al., 2022). Thus, using supervised machine learning models is recommended for other types of sediment load modeling. A full review of application of AI-based models for modeling suspended sediment load has addressed current views and future directions for using these models (Tao et al., 2021). Due to the advantages of data mining approaches for predicting sediment loads (Salih et al., 2020), deeper focus on their application for sediment transport and sediment yield studies is necessary. In fact, machine learning models are complex which means they can be used for different spatial and temporal scales. Moreover, different methods can be applied in the development of a machine learning model which are highly effective for the accuracy of the model. Hence, developing machine learning models in water quality simulation as well as sediment yield assessment is still a fresh research field which requires more study.

Hybrid machine learning models such as hybrid ANFIS models have been highlighted to improve the capabilities of machine learning models (Ojha et al., 2019). Applying hybrid machine learning models in environmental engineering is one of the novel methods highlighted in recent years which means its applicability should be investigated for sediment yield assessment as well. Furthermore, engineers desire quick models with minimum data requirements to provide a rough estimation of sediment yield due to agricultural development scenarios as well as climate change scenarios.

The two foregoing research gaps are the main motivations of the current study. A new architecture is proposed for simulating sediment yield by an AI method in which a broad range of hybrid machine learning models have been evaluated to select the best approach. The first novelty of the current study is to develop a new form of data driven model by using hybrid adaptive neuro fuzzy inference systems which can be applied for sediment yield prediction at the catchment scale. Moreover, the novel model is able to predict the impact of afforestation scenarios on the mitigation of sediment yield from catchments which is one of the important environmental challenges. Three objectives are identifiable in the current study as follows:

1 Develop a novel structure for annual assessment of sediment yield at the catchment scale in which minimal data requirements have been considered to have an inexpensive and straightforward model.
2 ANFIS hybridized using evolutionary algorithms to improve the accuracy and efficiency of the machine learning models for sediment yield assessment.
3 Adding a forest index to the data-driven model of sediment yield to predict impacts of reforestation scenarios at the catchment scale.

2. Application and methodology

2.1. Case study

The Talar River basin located in Mazandaran Province in the northern part of Iran was selected as a case study, because it is a sensitive basin in terms of sediment yield. This basin is located in a highly populated region. In fact, there has been a lot of migration to this basin in recent years due to the droughts in the southern parts of Iran. In other words, many people are inclined to settle in Mazandaran province owing to temperate weather and higher precipitation. Therefore, increases in agricultural and industrial activities is one of the challenges in the area, which can adversely affect environmental values quickly. Deforestation due to expanding agricultural land is the main driver of increasing sediment yield at present and in future years. In the context of impacts of sediment yield on the ecological status of catchments such as downstream aquatic habitat, sediment yield modeling is of particular importance in this area. It should be noted that this area has been naturally covered by evergreen and seasonal forests.

As agricultural activities have increased in recent decades, one of the current environmental concerns is reduction of existing forests. In fact, the area of forests in the basin has a great effect on the amount of sediment transport to downstream areas. Hence, the main application of the sediment model in this area is to investigate the effect of reduced forest area on the sediment yield because simulating future scenarios of deforestation is a key component in environmental management of the basin. Preliminary studies have shown that sediment yield in sub-catchments protected from logging is much less compared to the sub-catchments where deforestation has occurred. Therefore, a forest index was considered as one of the model's input parameters as explained in the previous section. Equation (1) shows the mathematical definition of this index:

$$\text{Forest index} = \frac{\text{Area of all forests in the catchment}}{\text{Total area of catchment}} \tag{1}$$

Figure 1 shows the location of Talar River basin in Mazandaran Province. This area consists of 21 sub-catchments. It should be noted that the basin map in Fig. 1 is generated by the Soil and Water Assessment Tool (SWAT) as a conventional hydrological model. More details regarding this model is out of the scope of the current study and has been addressed by Gassman et al. (2014). Due to the need for sufficient data for developing a machine learning model, each sub-catchment has been taken into account in the model training and testing processes. In fact, the amount of annual sediment yield from each sub-catchment during the training period of the model measured at the hydrometric stations or by the research team was used to train the data driven model. According to the structure of the model described in the previous section, there are 4 inputs in the current case study including area, average slope, rainfall, and forest index in each sub-catchment. It should be noted that the average annual rainfall in each sub-catchment was considered in the development of the model. Figure 2 shows the average annual rainfall of the Talar River basin in the training period. More details on the methodology of the field studies have been presented by Walling (2017).

According to the model's technical considerations for the inputs, it was necessary to pre-process the inputs before developing the main model. One of the main inputs of the sediment model is the average slope in each sub-catchment in which a digital elevation model (DEM) is needed to produce the slope map. Figure 3 shows the DEM as well as the slope map generated using GIS. Variation of elevation in the study area is highly significant. The south of this basin is located in a mountainous area. In contrast, the north of the basin is located in the coastal area which means the variation of elevation between −19 m to 3977 m is reasonable. The DEM shows that the slope can remarkably affect sediment yield especially in the upstream sub-catchments. Using the existing DEM, a slope map was generated as displayed in Fig. 4. The slope of the basin varies between 0 and 75°, which clearly indicates that many of the upstream sub-catchments have steep slopes, while the downstream sub-catchments close to the sea have mild slopes. According to the generated map, the area of each sub-area was calculated, which is one of the model's inputs. Moreover, using existing land use map and aerial image shown in Fig. 1, the forest index was

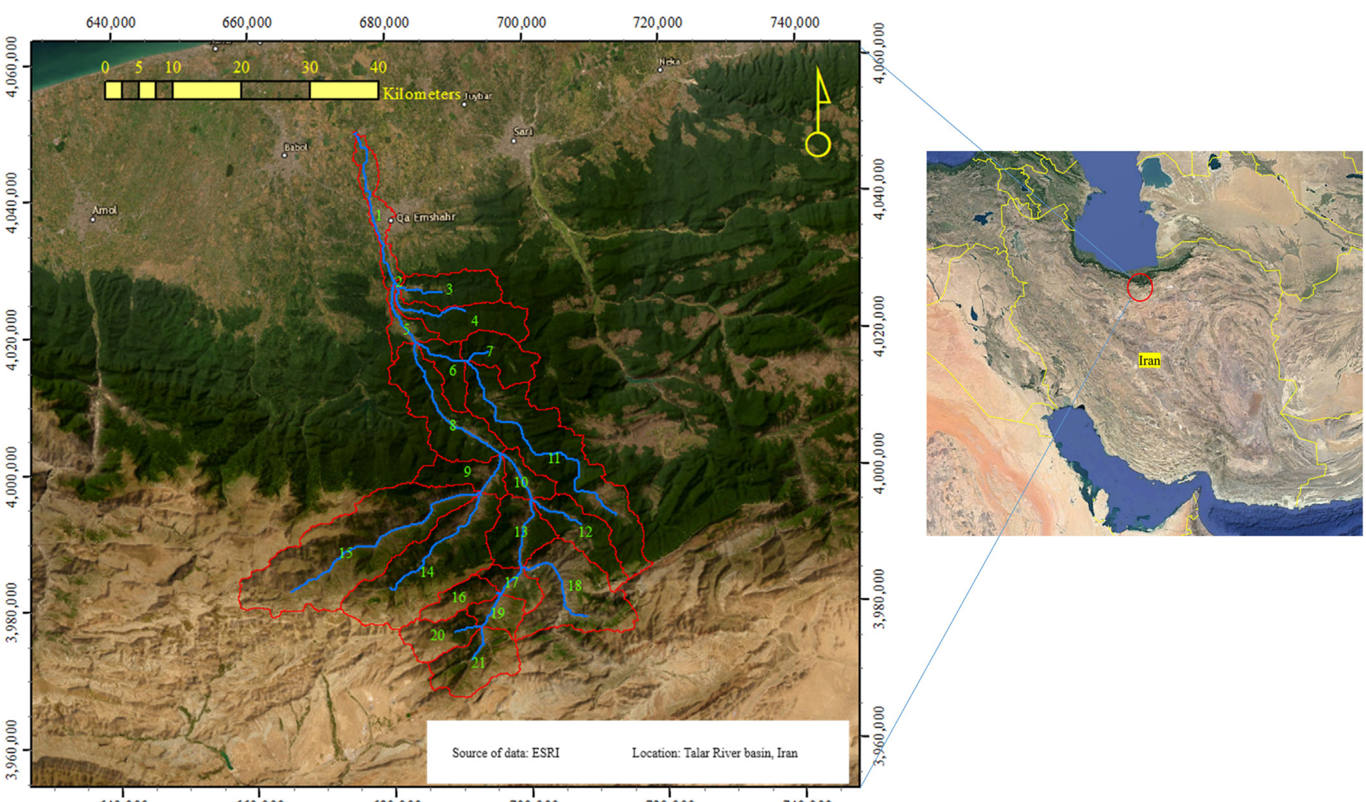

Fig. 1. Location of the study area and sub-catchments of the Talar River basin.

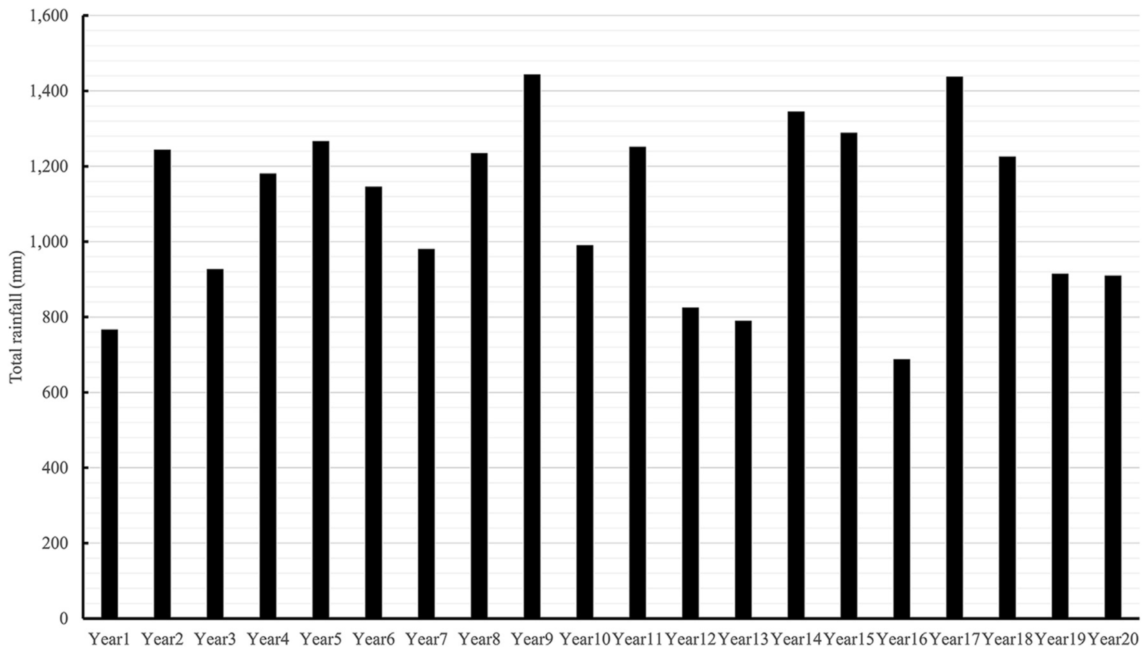

Fig. 2. Average annual rainfall in the Talar River basin in the training period (1992–2012).

calculated for each sub-catchment. It is necessary to mention that a 20-year period was utilized in the model training phase and a 5-year period was utilized in the model testing phase.

It is necessary to provide more details on the data and parameters of the models for simulation of the sediment yield in the current case study. Overall, 420 samples were available throughout the catchment for training and testing of the model. Based on recommendations for using data-driven models, 75% of available data or 315 samples were used for training of the model which means rest of available data was applied for testing the model. The results of the testing process are presented in the results.

2.2. Architecture of the model

ANFIS was used to simulate sediment yield at the catchment scale. According to Fig. 5, the structure of the model consists of five layers, in which the first layer gives the membership function. In the second layer, which contains fixed nodes, all received signals are multiplied and transferred to the third layer, which calculates the normalized firing of each fuzzy rule. Then, in the fourth layer, there are adaptive parameters which will be tuned during the model training process. Finally, a single node is calculated as the last layer (output) sum of all input signals. It should be noted that this method has advantages over the partitioning method. More details regarding clustering methods in the ANFIS model have been described in the literature (Awan & Bae, 2014; Yeom & Kwak, 2018).

Figure 5 shows the structure of the model developed to simulate the sediment yield at the outlet of the catchment. Four key parameters are selected as inputs of the model. It is necessary to mention that selecting input parameters in machine learning models matters because many parameters might play a role in the sediment yield of a catchment. Considering all these parameters in a machine learning model is practically impossible due to computational limitations. Hence, inserting key effective parameters is the best option to develop an efficient model. According to hydrological investigations at the scale of a catchment in previous studies (Ali et al., 2021; Gwapedza et al., 2021), four key parameters were selected which are significantly affect the sediment yield including catchment area, catchment average slope, forest index, and average annual rainfall on the catchment. Some parameters (such as catchment area) do not need further description. However, more explanations are needed for some terms such as the forest index.

The Talar River basin located in Iran consists of evergreen and seasonal forests which means forest area is a key indicator of changing sediment yield. It should be noted that this index might not be applicable in all basins. In other words, this factor was defined in the model based on the existing challenge in the case study which was land degradation due to deforestation. More explanations regarding the physical characteristics of the current case study are provided in the next section.

The importance of other parameters should be described as well. Increasing the area of the catchment enhances sediment yield which implies catchment area plays a key role to increase downstream sediment transport. Furthermore, average slope of the catchment is another parameter that greatly affects the amount of sediment yield. Increasing average slope of a catchment increases sediment yield especially in significant rainfall events. Total rainfall depth is considered in the input parameters as well because rainfall is the main driver of sediment transport in a basin.

Many other parameters might have insignificant or minor effects on the amount of sediment. However, it is impossible to consider those input parameters because inclusion of these parameters escalates complexities and weakens the efficiency of the model.

The output of the proposed model is sediment yield in the unit area (Mg/ha). In fact, the developed model can estimate the average amount of sediment yield from each hectare which means total sediment yield should be calculated based on total area of the catchment. The proposed model can be used at the catchment scale and the availability of adequate recorded data is able to guarantee model. In the current study, using a hybrid model was done in which the training process was accomplished using evolutionary algorithms. Given the nature of the training process which is a type of optimization, upgrading the optimization method can significantly affect the accuracy and reliability of the model. To this end, a

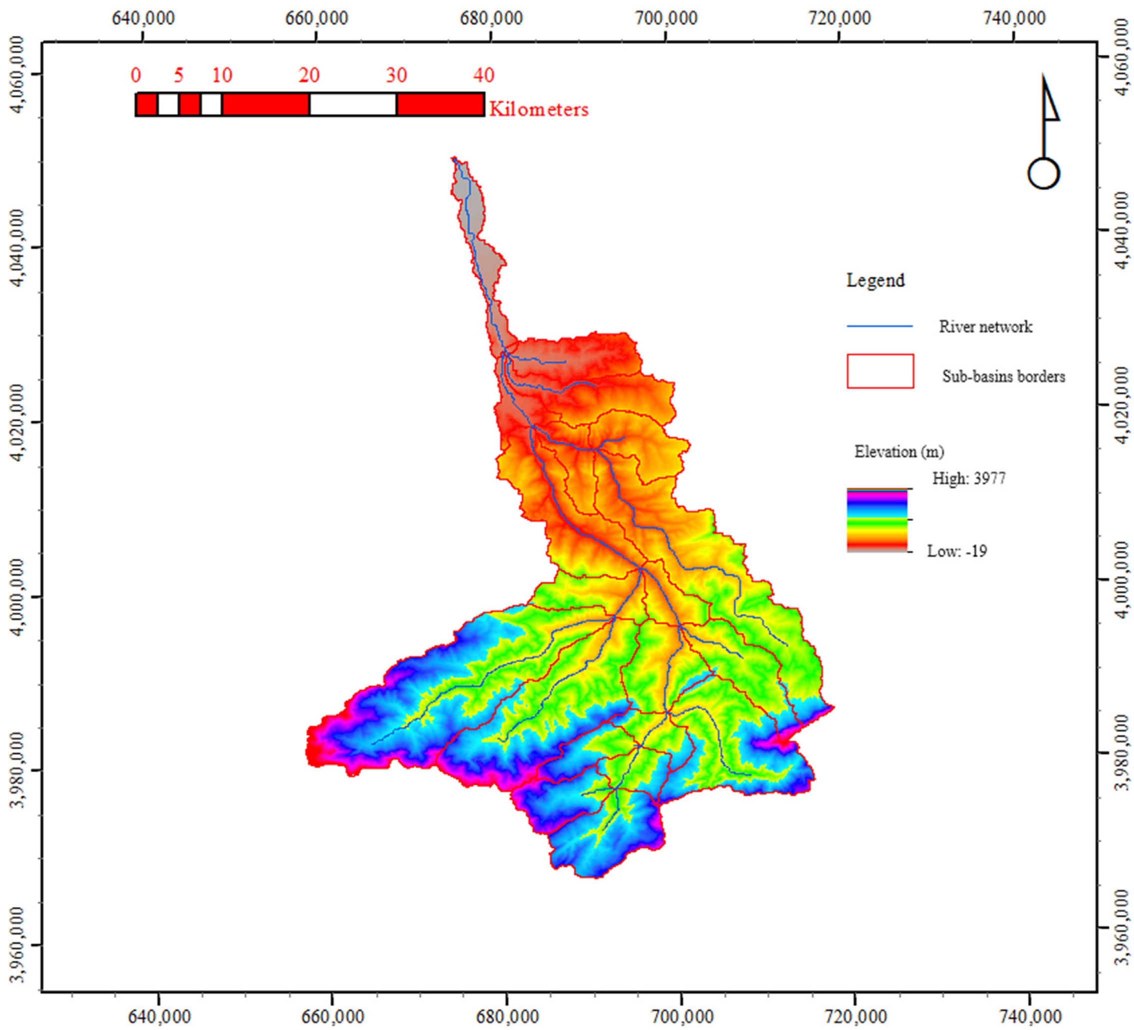

Fig. 3. Digital elevation model of the Talar River basin.

wide range of evolutionary algorithms were used for training the sediment machine learning model. The model was designed to assess sediment yield annually which means total annual rainfall was considered as the input of the model. More details regarding evolutionary algorithms for hybridizing ANFIS-based models are presented in the next section.

Apart from hybrid models considering evolutionary algorithms, a conventional training algorithm (backpropagation + least square) was applied to compare results of the hybrid models as well. More details on this algorithm have been addressed in Méndez and de los Angeles Hernandez (2009). In Fig. 5, *inputmf* is a membership function of inputs which is a Gaussian function including 11 sub-functions from very low to very high. In contrast, *outputmf* is membership function of output (sediment yield) which is a triangular function.

2.3. Hybrid models

Several hybrid models were developed in which evolutionary algorithms were utilized as the trainer of the machine learning model. Table 1 lists the models and gives a brief description on each model. The number of iterations were considered as the termination criterion for the training process through the evolutionary algorithms. 10,000 iterations were done for convergence of the model to provide the best results. However, log files of the training process indicated that 5,000 iterations can be adequate for properly convergence of the model. Moreover, different numbers of population were tested for the models. Based on the current tests, the number of population were defined as 100 in the process of training models. The subtractive clustering method was used in the development of the ANFIS-based model in which 11 membership functions were defined for each input parameter. The user-defined parameters for each algorithm were defined based on the recommendations in the available references in Table 1.

2.4. Statistical indices

Each model definitely needs some statistical indices to measure its performance compared with the observations or recorded data. In fact, reliable model performance could be guaranteed, if statistical indices corroborate its robustness. In the current study, three statistical indices were applied including the Nash–Sutcliffe efficiency (NSE) generally used for hydrological models (Knoben et al., 2019), root mean square error (RMSE) as a known statistical index for all models (Hodson, 2022) and vulnerability index (VI) used in water resources management studies (Sedighkia & Abdoli, 2022).

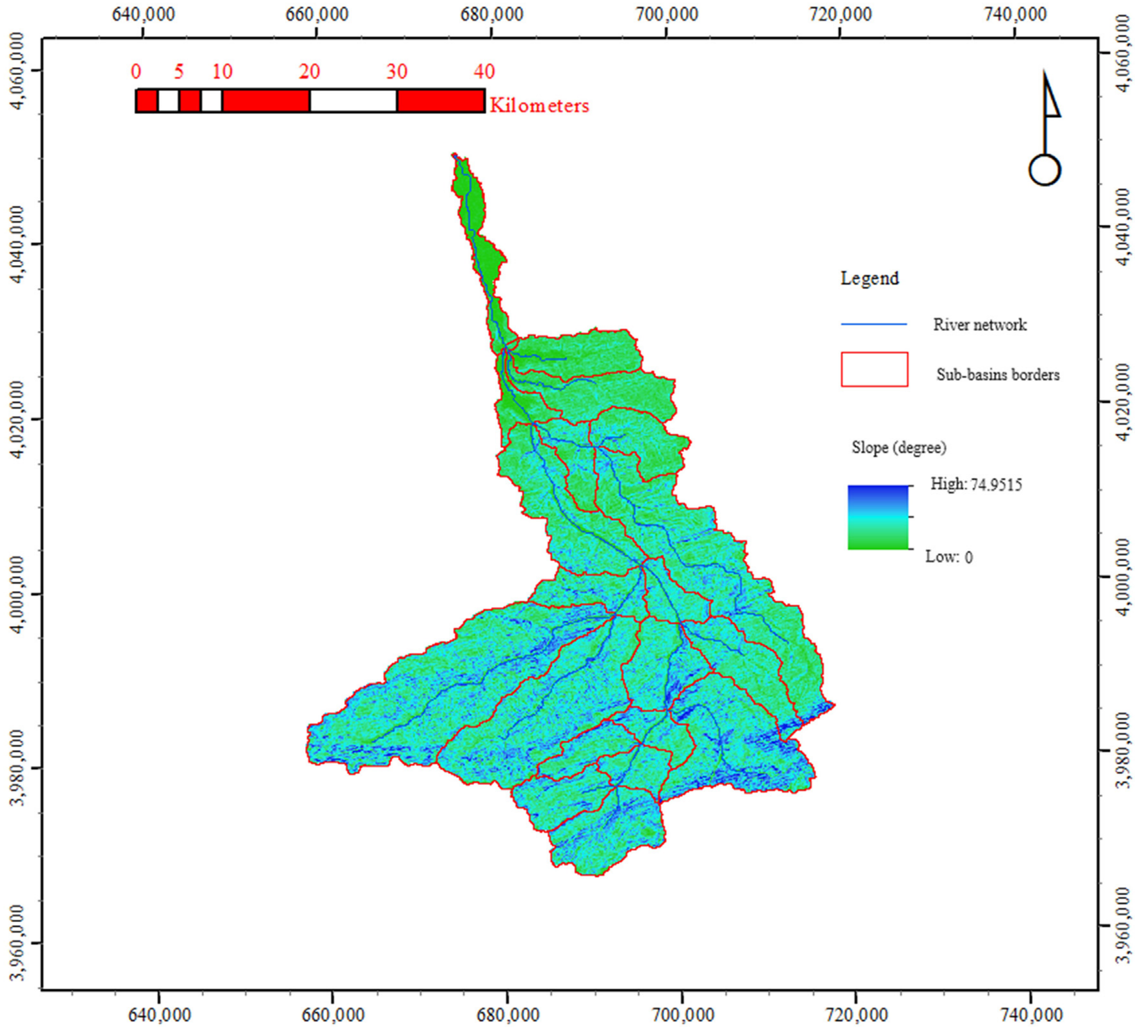

Fig. 4. Slope map of the Talar River basin.

The following equations display the mathematical definition of these indices in which M is modeled data and O is observed or recorded data. Moreover, m means average and T is the total number of simulated values.

$$\mathrm{RMSE} = \sqrt{\sum_{t=1}^{T} \frac{(M_t - O_t)^2}{T}} \tag{2}$$

$$\mathrm{VI} = \mathrm{Max}_{t=1}^{T} \mathrm{ABS}\left(\frac{M_t - O_t}{O_t}\right) \tag{3}$$

$$\mathrm{NSE} = 1 - \frac{\sum_{t=1}^{T} (M_t - O_t)^2}{\sum_{t=1}^{T} (O_t - O_m)^2} \tag{4}$$

3. Results

First step, the results of sediment yield modeling should be displayed using hybrid machine learning models. Figures 6–8 display the simulation results in the 5-year testing period for all sub-catchments as well as Talar River catchment. Due to the development of several models, hybrid models are shown in two figures. Moreover, Fig. 8 shows the results of the conventional ANFIS model, which applied a hybrid algorithm (backpropagation + least squares) for model training compared with the recorded sediment yield. The performance of the different models varies significantly. Hence, using hybrid models is remarkably effective, but yields varying results which means applying a machine learning model cannot be practical without preliminary evaluation of a wide range of models. As discussed in the previous section, interpretation and analysis of the results generated by different models require use of different statistical indices. In fact, it is difficult to analyze or interpret the results of the model by observational comparison. Therefore, it is necessary to use statistical indices to understand the differences among models to simulate sediment yield at the catchment scale.

Table 2 lists the statistical indices including the NSE, RMSE, and VI used in the current study. In other words, the combination of these three indices can be applied as a criterion to choose the best model. According to Table 2, models such as ABC and DE performed poorly because the NSE, which is an important index, must be greater than 0.5 for the results of the model to be acceptable. In these models, the NSE index is less than 0.5 which means these three hybrid models are not reliable for simulating sediment yield. Also, the NSE of HS model is less than 0.5. Therefore, this model is not reliable to simulate sediment yield at the catchment scale.

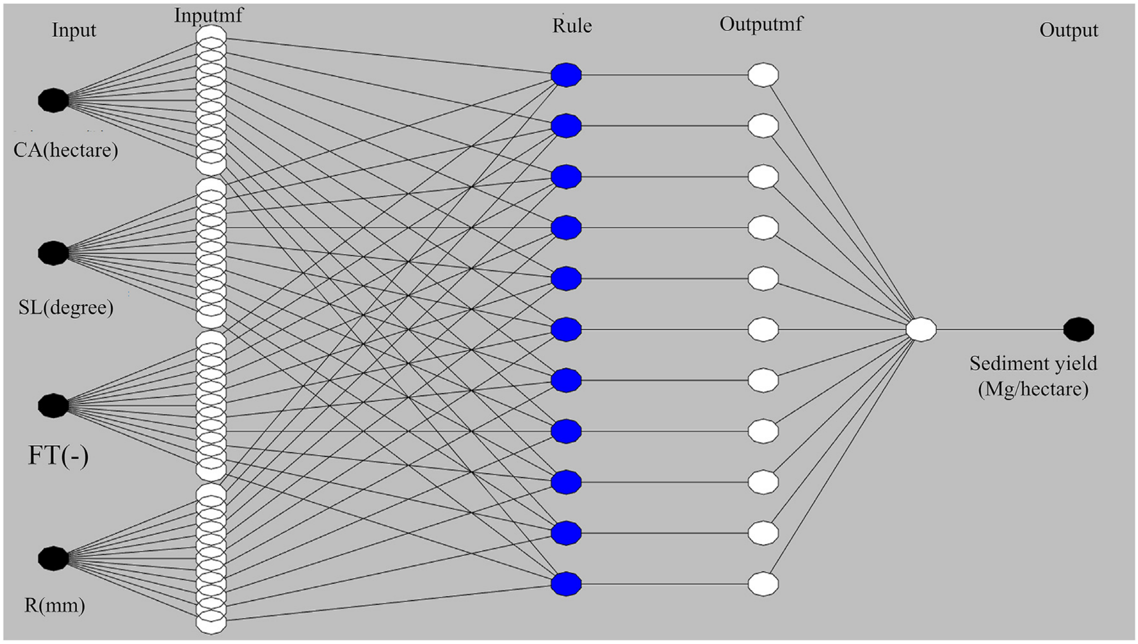

Fig. 5. Architecture of sediment yield prediction model proposed in the current study (CA, SL, FT and R are area of the catchment, average slope of the catchment, forest area to total area and annual rainfall).

Table 1
Details regarding the hybrid models.

Model	Computational time	Reference for evolutionary algorithms
ABC-ANFIS	Trained by artificial bee colony (ABC) algorithm inspired from foraging behavior of honey bees	Hussain et al. (2020)
BBO-ANFIS	Trained by biogeography-based optimization (BBO) which uses mathematical models of biogeography including the evolution of new species, the migration of species and the extinction of species	Li et al. (2022)
CA-ANFIS	Trained by cultural algorithm (CA) inspired from societal evolution	Phatai et al. (2020)
DE-ANFIS	Trained by differential evolution (DE) which applies multidimensional real-valued functions	Pan et al. (2020)
GA-ANFIS	Trained by genetic algorithm inspired from Charles Darwin's theory of natural evolution	Katoch et al. (2021)
HS-ANFIS	Trained by harmony search (HS) algorithm inspired from improvisation of musicians	Dubey et al. (2021)
ICA-ANFIS	Trained by imperialist competitive algorithm (ICA) as the counterpart of classic algorithms	Lei et al. (2020)
IWO-ANFIS	Trained by invasive weed optimization (IWO) algorithm inspired from the behavior of weed colonies	Movassagh et al. (2021)
PSO-ANFIS	Trained by particle swarm optimization (PSO) inspired from the movement of organisms in a bird flock or fish school	Pradhan et al. (2022)
ACO-ANFIS	Trained by ant colony optimization (ACO) inspired from the behavior of ant colonies	Akhtar (2019)
SCE-ANFIS	Trained by shuffled complex evolution (SCE) algorithm which applies geometric operations to find optimal solutions	Naeini et al. (2019)

Outputs corroborate that the NSE of the conventional ANFIS model is less than 0.5 though the NSE is very close to 0.5 which means its performance is not very poor. However, by considering the criterion of 0.5 for NSE in the current study, this model should be excluded for estimating sediment yield. In fact, the current study highlights that using conventional training methods might not be a good option to generate a data driven model regarding sediment yield assessment.

The NSEs of the other remaining models including BBO, CA, GA, ICA, IWO, PSO, ACO, and SCE are greater than 0.5, which means their performance might be acceptable. Among all acceptable models, the NSEs of some models are close to 1. If the NSE index is equal to 1, it means perfect agreement between the modeled value and the observation data, which is not possible practically. In fact, it is not possible to develop a perfect model pragmatically. Outputs of the current study confirm that NSEs of some models such as PSO, SCE, GA, BBO and IWO are very close to 1 which means these models have highly potential to be accurate in simulating sediment yield. Thus, the other two indices RMSE and VI, should be taken into consideration to choose the best model. The RMSEs of the four models including GA, PSO, SCE and IWO are lower than 1 Mg/ha which implies these models have much less error than other models. In the current study, RMSE less than or equal to 1 was considered as a criterion in the second stage to select the best model. According to this criterion, the foregoing models can be the best models for sediment yield assessment. The third criterion is to use the VI index to measure the performance of the models. According to this index, the VI of PSO is significantly less than that for the other models, which means its performance is more reliable. Therefore, the PSO model can be selected as the best model to estimate the sediment yield at the catchment scale.

It is necessary to understand the impacts of different parameters on the sediment yield because it might be helpful for defining sediment management scenarios in the current case study. However, this analysis could be helpful in other case studies as well. In Fig. 9, the area of the sub-catchment (defined as in1 in Fig. 9) is

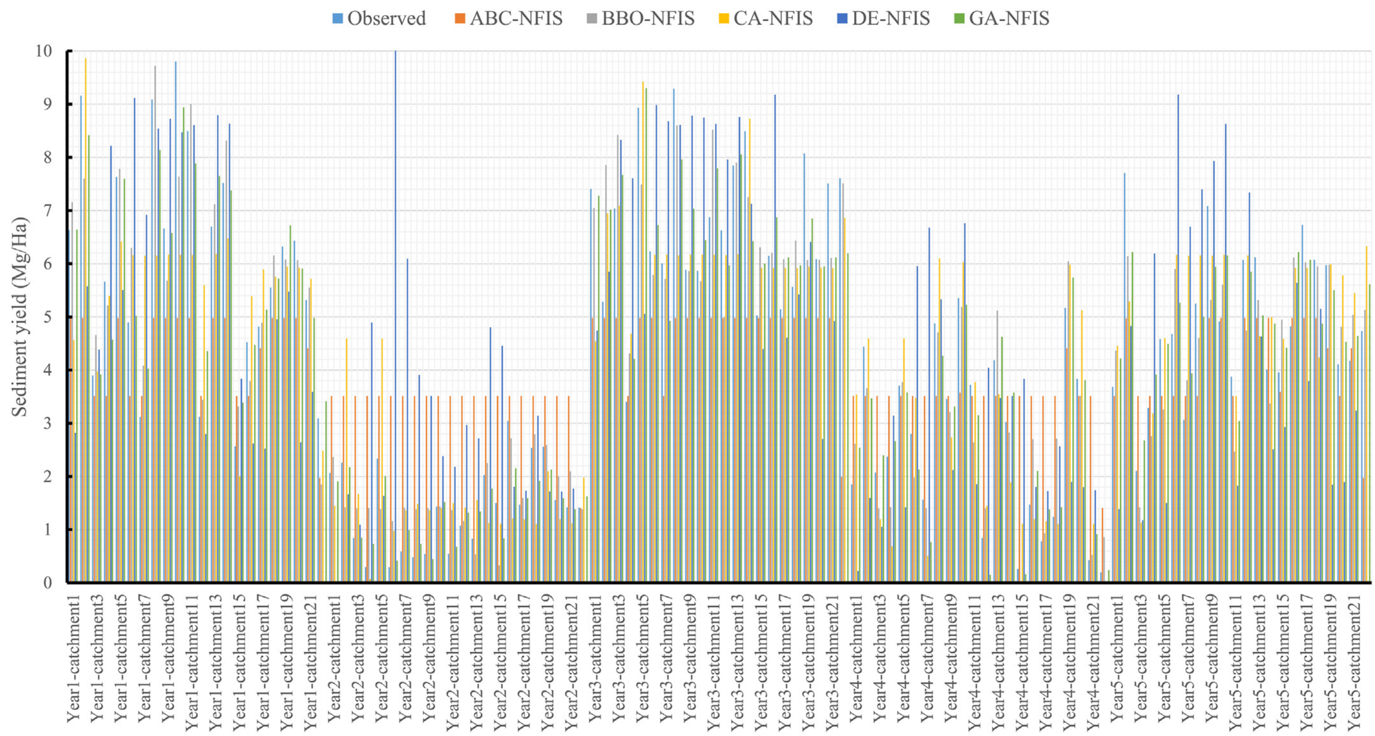

Fig. 6. Performance of the hybrid models (group 1).

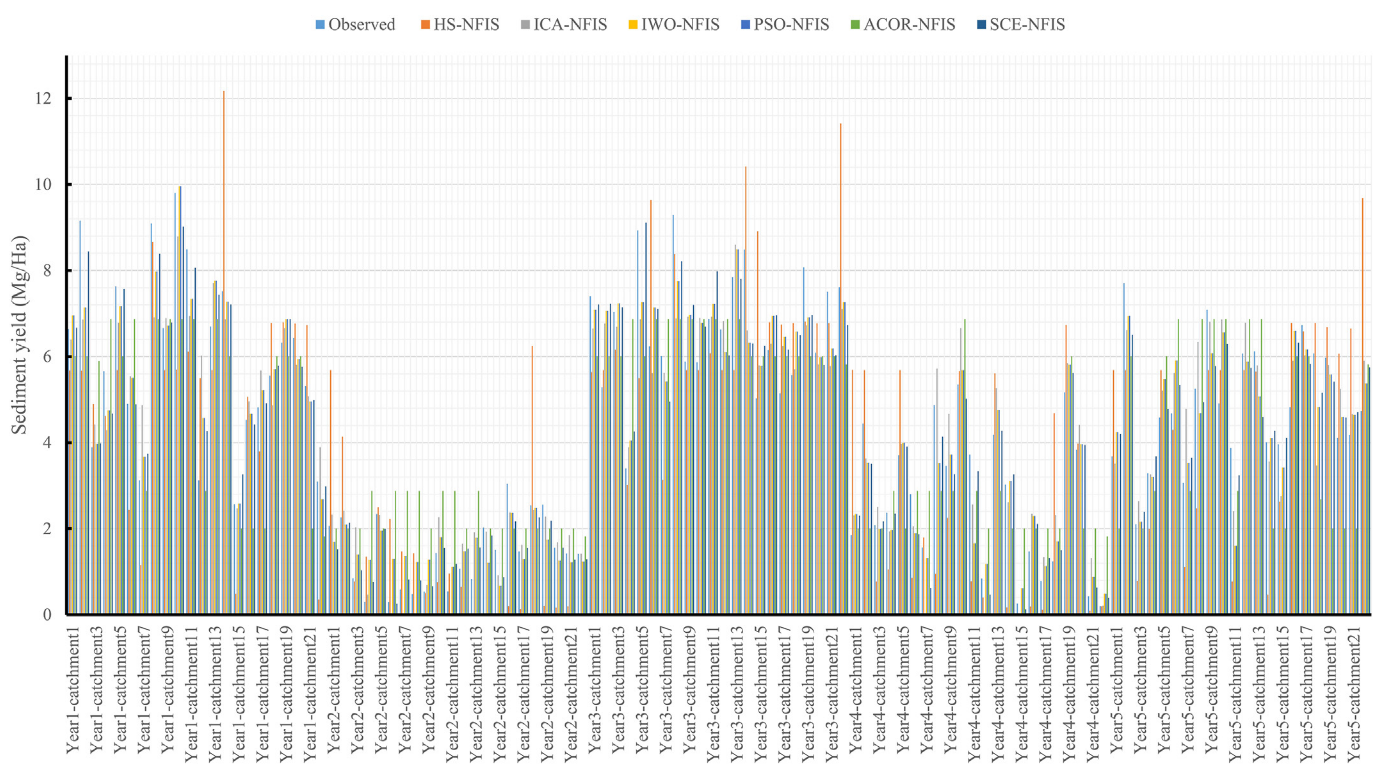

Fig. 7. Performance of the hybrid models (group 2).

selected as the basic parameter effective on the sediment yield as presented in the previous section. Then, the impact of other inputs of the model is plotted with respect to the area of sub-catchment. In these pseudo-color graphs, in2, in3 and in4 are the average slope of sub-catchment, forest index, and annual average rainfall, respectively. Two important points could be concluded from these graphs. First, the impacts of slope, forest area, and annual rainfall could be highly tangible when the area of sub-catchment increases. In other

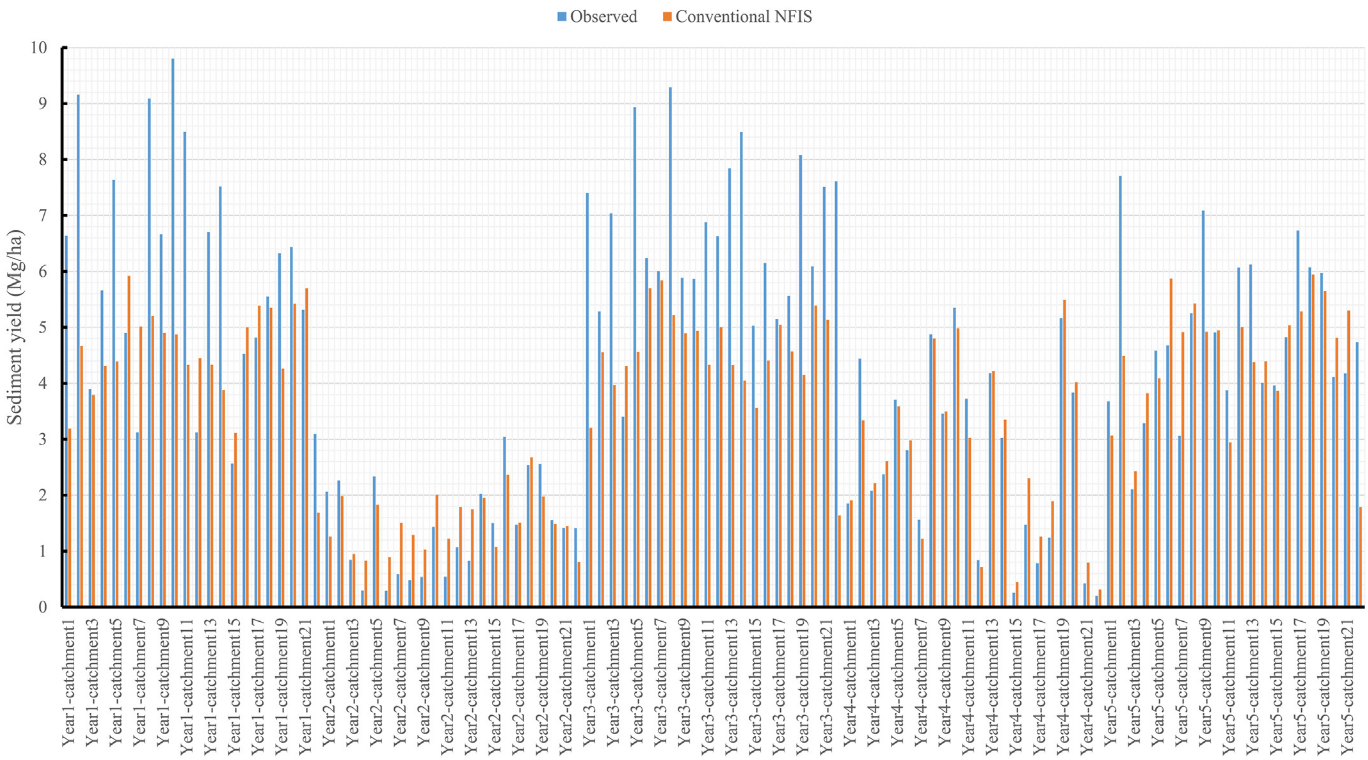

Fig. 8. Performance of conventional ANFIS models.

words, land management should be highlighted in larger catchments. Furthermore, no parameter is dominant in terms of impact on the sediment yield in the current case study which means simultaneous consideration of all effective key parameters is needed.

4. Discussion

Discussion on the strengths and weaknesses of the models as well as the computational strengths and limitations can be useful to select the best options in future studies. It is necessary to discuss on superiority of the developed machine learning models to estimate the amount of sediment yield. In other words, it is necessary to explore the advantages of these models over the conventional hydrological physically based models. In terms of the technical issues of available models for simulating sediment yield, it should be noted that conventional hydrological models such as SWAT require more parameters such as soil maps as the inputs to simulate sediment yield which might not be available in all cases. In contrast, the developed machine models only have few key inputs which means implementation of these models could be easier. Therefore, using the developed machine learning model is superior in terms of the number of required inputs compared to the conventional hydrological models. In other words, acceptable results can be obtained using less effort for data collection and model, which is an important advantage.

One of the weaknesses of the models developed in the current study at the catchment scale is the need to develop independent models for different water quality parameters which means more effort is required to develop a modeling package to estimate all water quality parameters. Developing a combined model with multiple outputs might not be efficient computationally. Therefore, several models might be used to estimate the required parameters. In the present study, a model was developed to estimate the amount of sediment yield in the basin. However, other physical parameters of the basin might be important as well based on the purposes of the projects. In conventional hydrological models such as SWAT, which have been frequently utilized in different countries for studying catchments, the model is able to simulate different parameters simultaneously such as discharge at the outlet as well as different water quality parameters. Hence, those models could be superior to machine learning models if the goal is to simulate flow time series. Machine learning models can be significantly quicker and need less input data, if direct assessment of quality parameters such as sediment yield is the objective. In other words, these types of machine learning models might have acceptable performance with less effort for finalizing the models.

Limited studies have been done regarding application of machine learning models in the field of sediment yield assessment in catchments. These studies have been designed to assess suspended sediment, bed load, or total sediment yield. It should be noted that the focus of the current study is to assess potential total sediment

Table 2
Statistical indices for the different models.

Model	NSE	RMSE	VI
ABC-ANFIS	0.35	2.01	5.62
BBO-ANFIS	0.87	0.89	2.57
CA-ANFIS	0.75	1.24	3.63
DE-ANFIS	−0.19	2.72	9.73
GA-ANFIS	0.92	0.71	2.07
HS-ANFIS	0.29	2.09	4.97
ICA-ANFIS	0.84	1.01	2.90
IWO-ANFIS	0.89	0.84	2.27
PSO-ANFIS	0.92	0.68	1.90
ACO-ANFIS	0.60	1.57	3.97
SCE-ANFIS	0.92	0.71	2.18
Conventional ANFIS	0.48	1.80	5.97

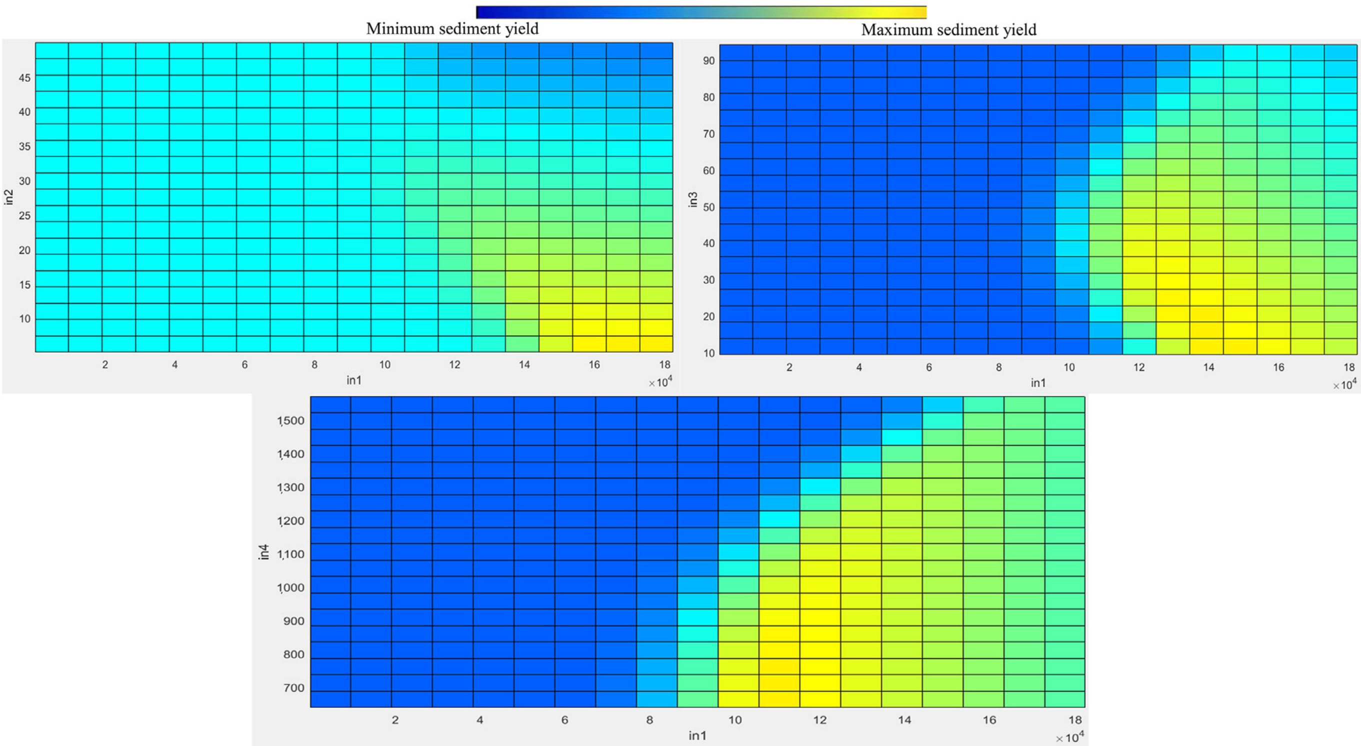

Fig. 9. Impact of different inputs with respect to area of catchment using pseudo-color graph (in1 to in4 are area of sub-catchment, average slope, forest index, and annual rainfall, respectively).

transport to downstream in the catchment annually. Thus, it is necessary to compare the results of the current study with those of studies that have been done in this regard to have a better understanding on future research trends. Based on exploring previous studies, the accuracy of the hybrid models developed in the current study is higher than previous data driven models though the conventional neural network models such as feed forward neural networks can be acceptable to assess sediment yield (Meshram et al., 2019).

Another point which should be considered is the contradictory outputs in application of machine learning models for assessing sediment yield. The current study corroborates the conclusion of the previous studies for using supervised approaches in the sediment transport modeling (Tao et al., 2021). Some previous studies found machine learning models such as support vector machine, are more accurate options (Dey et al., 2020). Therefore, it seems that catchment characteristics can affect the model performance. Due to the complexities of the effect of different parameters on the sediment yield, identifying the best approach is an arduous task which means the best approach is to apply a broad range of models in each case study for selecting the best model considering statistical indices.

Apart from the technical aspects, computational aspects matter in the application of machine learning models as well. Therefore, it is necessary to discuss on these aspects of these models as well as technical aspects. Computational complexities are important aspects which can be a hindrance for using these types of models practically because engineers and environmental managers who are the end users of the sediment yield models require to use the models for long-term periods or numerous simulations. In general, experts are reluctant to use complex models because the cost of using complex models will be high and it practically limits application of these models for different scenarios. Based on the scientific definition, computational complexity includes the time and memory required for implementing a machine learning model. Therefore, the lower the computational complexity, the more applicable the model is.

The current assessment demonstrates that required memory for all models is approximately the same which means computational time is a key factor for comparing the models in terms of computational complexities. It should be noted that the computational time for the testing process is not considerable which means computational complexities in the training process were limited to develop efficient models. Table 3 lists the computational time required for each developed model in the training phase. The performance of the models is completely different which implies it is a vital factor to select an efficient model. In other words, one of the parameters to choose a suitable model is to apply Table 3 to select a model with lower computational time. Models such as HS-ANFIS are much less complex than other models. In fact, the Harmony Search algorithm has considerable ability to find the optimal result in a short time. However, the reliability assessment of this model

Table 3
Computational time of different models in the training process.

Model	Computational time (min)
ABC-ANFIS	210
BBO-ANFIS	243
CA-ANFIS	265
DE-ANFIS	112
GA-ANFIS	325
HS-ANFIS	38
ICA-ANFIS	233
IWO-ANFIS	271
PSO-ANFIS	242
ACO-ANFIS	169
SCE-ANFIS	218
Conventional ANFIS	134

(Table 2) indicated that it is not appropriate to assess sediment yield in the current case study. Therefore, this model should not be selected as a superior model for future studies.

Among the models which are highly reliable to assess sediment yield, PSO-ANFIS has lower computational time in the training phase. Therefore, this model can be claimed as a superior model considering both aspects of computational complexity and ability to generate acceptable outputs. One of the remarkable points of the current study is acceptable performance of the conventional ANFIS model in terms of computational time. In fact, this model can be trained in an acceptable time for assessing the amount of sediment yield in different scenarios. According to the modeling performance in Table 2, the NSE of this model is close to 0.5 which implies it has acceptable results to some extent. However, the generated results are not as accurate as models like PSO-ANFIS. In fact, despite the advantages of conventional training algorithms such as the hybrid algorithm (back propagation + least squares) in terms of computational time for training machine learning models, these types of models cannot be the best choice to simulate sediment yield due to lower accuracy compared to hybrid models.

Another important point for applying hybrid models is inability of evolutionary algorithms to find the global optimization. In fact, there is no certainty that the best optimal solution can be achieved using an evolutionary algorithm. Hence, using several hybrid models can be a solution to find the best response. In the current study, the performance of hybrid models is completely different. In fact, the performance of evolutionary algorithms for finding optimal coefficients in neural networks is different. One of the important outcomes of the current study is that use of one evolutionary algorithm for the development of a hybrid model cannot be a reliable solution to assess sediment yield. It is recommended to develop different models by using the algorithms considered in this study in other case studies.

Another noteworthy point is that the performance of evolutionary algorithms can be different in basins. Furthermore, their performance might not be similar when changing inputs to the model. In fact, the selection of model input parameters can effectively alter the performance of the evolutionary algorithm in model training. The evolutionary algorithms were applied in the current study to improve the accuracy and efficiency of the data driven sediment yield model. However, the results indicated that some algorithms such as HS have weakened the performance of the ANFIS model compared to the conventional models. All evolutionary algorithms cannot guarantee the global optimization or the best results of optimization corroborated in previous studies. Thus, the definite improvement from these algorithms even if all parameters of the algorithms cannot be expected are determined correctly. In fact, this is the main motivation for comparing and selecting the best algorithm.

It is important to discuss the limitations of the hybrid models. In fact, the developed architecture of sediment yield modeling is not usable in all cases and problems which means the purpose of the current study has a great influence on the useability of the model. The proposed models are developed to assess sediment yield considering annual average precipitation which means application of this model for smaller temporal scales might not generate acceptable results. However, if the goal of the study is to estimate annual sediment or long-term land management in a basin, the proposed model can generate brilliant results. If the goal of the project is to estimate the amount of sediment in flood events or similar short periods which means estimation of sediment yield in the short term, the structure of the model should be completely revised. Hence, one of the future research trends can be to apply this type of data driven models by changing the structure of the data driven model for shorter temporal scales or flood events. Another weakness of the proposed model is its inability to simulate river discharge. If there is a need for such a model, it is necessary to consider river discharge as the output of the model or to develop a parallel model in this regard. Moreover, the current study focused on the forest index as one of the land use indices. However, highlighting other types of land use indices in future studies is essential.

Among the important applications of the proposed models, its ability to simulate different scenarios of deforestation can be highlighted as well as different scenarios of nature-based solutions for restoring the basin. Moreover, simulating other characteristics of land use can be considered as an outcome in the case of changing the model according to the changes of the geographical conditions of the area. One of advantages of the proposed model is flexibility for different applications which means it can be used for a wide range of sediment yield problems applying minor changes in the architecture of the model. It should be noted that destruction of natural lands is one of the important environmental challenges in recent decades, which can have significant effects on environmental values. Due to the importance of forests for protecting the health of the planet's ecosystem, deforestation is one of the important signals of land degradation focused on in recent decades. In addition to the direct effects of deforestation such as damage to biodiversity and carbon capture, it will also have secondary effects on the catchment area where the forests are located. In fact, deforestation causes the degradation of soil quality as well as soil erosion, as a result of increasing sediment yield in the basin. In fact, modeling the amount of sediment yield can be an assisting tool for better land management.

To sum up, the current study proposed hybrid machine learning models as a robust alternative for hydrological based models to assess sediment yield. The proposed modeling framework is able to open new windows for using machine learning models in land management which means the structure of the model could be used for other problems in catchments for having a reliable and quick model. In fact, engineers can develop similar models for fast assessment of different scenarios for land management of basins.

5. Conclusions

The current study developed a novel structure of a data driven model to assess sediment yield at the catchment scale which needs some key parameters as the inputs. An ANFIS based model hybridized using evolutionary algorithms was applied as the modeling approach in the data driven model. According to the current case study results, PSO-ANFIS was selected as the best hybrid model to generate reliable results in terms of simulating annual sediment yield in the catchment. Furthermore, it is demonstrated that the performance of some hybrid machine learning models is more reliable compared with the conventional ANFIS based model in which a hybrid algorithm (back propagation + least squares) has been utilized as the training algorithm. Less required input data for developing the model and less time for simulation of different scenarios of land management are the most important advantages of developed data driven model compared to physically based catchment models such as SWAT. The main limitation of the proposed models is focus on the annual sediment yield which means the model is not usable for fine temporal scales. Moreover, the forest index is the only highlighted land use index. It is recommended to modify the models for applying to fine temporal scales as well adding other land use indices to the model.

Data availability

Some or all data and materials that support the findings of the current study are available from the corresponding author upon reasonable request after confirmation of the request by the data provider.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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